autogluon_each_location

October 6, 2023

[126]:
```python
import pandas as pd
import numpy as np




import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
 ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X




def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")


    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
 ↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
 ↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

    X_train_estimated["estimated_diff_hours"] =␣
 ↪X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
```

```
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train, location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train = convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="outer", left_index=True, right_index=True)

    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
```

```
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Processing location B…
Processing location C…
```

1 Feature enginering

[127]:

```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year


to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
```

```python
X_test.to_csv('X_test_raw.csv', index=True)
```

[128]:
```python
import autogluon.eda.auto as auto
auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",
 ↪sample=None)
```

train_data dataset summary

```
                           count  unique top   freq            mean  \
absolute_humidity_2m:gm3    92951    165                   6.017608
air_density_2m:kgm3         92951    293                   1.255435
ceiling_height_agl:m        72276  40993                2802.588135
clear_sky_energy_1h:J       92951  48602               515154.09375
clear_sky_rad:W             92951   7815                 143.101379
cloud_base_agl:m            84404  34862                1692.934692
dew_or_rime:idx             92951      3                   0.007025
dew_point_2m:K              92951    436                 275.237762
diffuse_rad:W               92951   2870                  39.495815
diffuse_rad_1h:J            92951  48553               142180.03125
direct_rad:W                92951   5296                  50.205021
direct_rad_1h:J             92951  41885                180740.1875
effective_cloud_cover:p     92951   1001                  67.013519
elevation:m                 92951      3                  11.401738
estimated_diff_hours        92951     26                   3.143516
fresh_snow_12h:cm           92951    125                   0.116175
fresh_snow_1h:cm            92951     39                    0.00963
fresh_snow_24h:cm           92951    161                   0.229894
fresh_snow_3h:cm            92951     70                   0.029001
fresh_snow_6h:cm            92951     96                   0.058069
hour                        93024     24                  11.501462
is_day:idx                  92951      2                   0.483341
is_in_shadow:idx            92951      2                   0.565384
location                    93024      3   A  34085
month                       93024     12                   6.290484
msl_pressure:hPa            92951    874                1009.502563
precip_5min:mm              92951     64                   0.005674
precip_type_5min:idx        92951      7                   0.083259
pressure_100m:hPa           92951    888                  995.81897
pressure_50m:hPa            92951    897                1001.949646
prob_rime:p                 92951    700                   0.756834
rain_water:kgm2             92951     11                   0.009677
relative_humidity_1000hPa:p 92951    788                  73.669556
sfc_pressure:hPa            92951    902                1008.107849
snow_depth:cm               92951    165                   0.193203
snow_melt_10min:mm          92951     19                   0.000275
snow_water:kgm2             92951     42                   0.090324
sun_azimuth:d               92951  69692                 182.386337
sun_elevation:d             92951  49376                  -1.207574
```

super_cooled_liquid_water:kgm2	92951	15	0.056944
t_1000hPa:K	92951	447	279.431061
total_cloud_cover:p	92951	1001	73.604263
visibility:m	92951	85686	33027.933594
weekday	93024	7	3.00215
wind_speed_10m:ms	92951	119	3.037911
wind_speed_u_10m:ms	92951	188	0.662565
wind_speed_v_10m:ms	92951	167	0.6824
wind_speed_w_1000hPa:ms	92951	3	-0.000016
y	93024	12430	287.019652
year	93024	6	2020.69495

	std	min	25% \
absolute_humidity_2m:gm3	2.714546	0.5	4.0
air_density_2m:kgm3	0.036608	1.139	1.23
ceiling_height_agl:m	2521.408447	27.799999	1037.099976
clear_sky_energy_1h:J	820525.5	0.0	0.0
clear_sky_rad:W	228.507324	0.0	0.0
cloud_base_agl:m	1790.963745	27.4	572.200012
dew_or_rime:idx	0.246032	-1.0	0.0
dew_point_2m:K	6.83461	247.300003	270.700012
diffuse_rad:W	60.647518	0.0	0.0
diffuse_rad_1h:J	215907.21875	0.0	0.0
direct_rad:W	112.946068	0.0	0.0
direct_rad_1h:J	401735.03125	0.0	0.0
effective_cloud_cover:p	35.044811	0.0	41.299999
elevation:m	7.877236	6.0	6.0
estimated_diff_hours	8.935328	0.0	0.0
fresh_snow_12h:cm	0.780374	0.0	0.0
fresh_snow_1h:cm	0.112621	0.0	0.0
fresh_snow_24h:cm	1.218249	0.0	0.0
fresh_snow_3h:cm	0.28067	0.0	0.0
fresh_snow_6h:cm	0.481389	0.0	0.0
hour	6.92022	0.0	6.0
is_day:idx	0.499725	0.0	0.0
is_in_shadow:idx	0.495709	0.0	0.0
location			
month	3.587269	1.0	3.0
msl_pressure:hPa	13.089046	944.299988	1001.400024
precip_5min:mm	0.033511	0.0	0.0
precip_type_5min:idx	0.384904	0.0	0.0
pressure_100m:hPa	13.008334	929.799988	987.799988
pressure_50m:hPa	13.067102	935.599976	993.900024
prob_rime:p	5.434649	0.0	0.0
rain_water:kgm2	0.042968	0.0	0.0
relative_humidity_1000hPa:p	14.328553	19.5	64.199997
sfc_pressure:hPa	13.128181	941.400024	1000.0
snow_depth:cm	1.254293	0.0	0.0

snow_melt_10min:mm	0.004312	-0.0	-0.0
snow_water:kgm2	0.250991	0.0	0.0
sun_azimuth:d	102.913605	0.008	92.794006
sun_elevation:d	24.010485	-49.979	-18.511
super_cooled_liquid_water:kgm2	0.111482	0.0	0.0
t_1000hPa:K	6.520342	257.899994	274.899994
total_cloud_cover:p	34.993042	0.0	51.700001
visibility:m	18319.150391	130.600006	15798.950195
weekday	2.000961	0.0	1.0
wind_speed_10m:ms	1.778505	0.0	1.7
wind_speed_u_10m:ms	2.808995	-7.3	-1.4
wind_speed_v_10m:ms	1.896996	-9.3	-0.6
wind_speed_w_1000hPa:ms	0.006502	-0.1	0.0
y	766.407785	-0.0	0.0
year	1.187172	2018.0	2020.0

	50%	75%	max \
absolute_humidity_2m:gm3	5.4	7.8	17.5
air_density_2m:kgm3	1.255	1.279	1.441
ceiling_height_agl:m	1803.25	3814.824951	12431.299805
clear_sky_energy_1h:J	4544.899902	778247.25	3006697.25
clear_sky_rad:W	0.0	220.949997	835.299988
cloud_base_agl:m	1128.550049	2016.699951	11688.900391
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	275.0	280.5	293.799988
diffuse_rad:W	0.0	66.0	340.100006
diffuse_rad_1h:J	9951.700195	236502.75	1182265.375
direct_rad:W	0.0	29.0	684.299988
direct_rad_1h:J	0.0	113366.25	2445897.0
effective_cloud_cover:p	80.800003	99.300003	100.0
elevation:m	7.0	24.0	24.0
estimated_diff_hours	0.0	0.0	39.0
fresh_snow_12h:cm	0.0	0.0	37.400002
fresh_snow_1h:cm	0.0	0.0	7.1
fresh_snow_24h:cm	0.0	0.0	37.400002
fresh_snow_3h:cm	0.0	0.0	20.6
fresh_snow_6h:cm	0.0	0.0	34.0
hour	12.0	17.0	23.0
is_day:idx	0.0	1.0	1.0
is_in_shadow:idx	1.0	1.0	1.0
location			
month	6.0	10.0	12.0
msl_pressure:hPa	1010.299988	1018.599976	1044.099976
precip_5min:mm	0.0	0.0	1.38
precip_type_5min:idx	0.0	0.0	6.0
pressure_100m:hPa	996.799988	1004.900024	1030.900024
pressure_50m:hPa	1002.900024	1011.099976	1037.300049
prob_rime:p	0.0	0.0	97.199997

rain_water:kgm2	0.0	0.0	1.4
relative_humidity_1000hPa:p	76.0	85.099998	100.0
sfc_pressure:hPa	1009.0	1017.200012	1043.800049
snow_depth:cm	0.0	0.0	18.299999
snow_melt_10min:mm	0.0	-0.0	0.18
snow_water:kgm2	0.0	0.1	6.9
sun_azimuth:d	179.526001	271.503479	359.997009
sun_elevation:d	-0.99	15.538	49.917999
super_cooled_liquid_water:kgm2	0.0	0.1	1.4
t_1000hPa:K	278.700012	283.899994	303.299988
total_cloud_cover:p	94.800003	100.0	100.0
visibility:m	37350.300781	48679.550781	76737.796875
weekday	3.0	5.0	6.0
wind_speed_10m:ms	2.7	4.1	15.2
wind_speed_u_10m:ms	0.3	2.5	12.2
wind_speed_v_10m:ms	0.7	1.9	9.0
wind_speed_w_1000hPa:ms	0.0	0.0	0.1
y	0.0	172.92	5733.42
year	2021.0	2022.0	2023.0

	dtypes	missing_count	missing_ratio	raw_type	\
absolute_humidity_2m:gm3	float32	73	0.000785	float	
air_density_2m:kgm3	float32	73	0.000785	float	
ceiling_height_agl:m	float32	20748	0.223039	float	
clear_sky_energy_1h:J	float32	73	0.000785	float	
clear_sky_rad:W	float32	73	0.000785	float	
cloud_base_agl:m	float32	8620	0.092664	float	
dew_or_rime:idx	float32	73	0.000785	float	
dew_point_2m:K	float32	73	0.000785	float	
diffuse_rad:W	float32	73	0.000785	float	
diffuse_rad_1h:J	float32	73	0.000785	float	
direct_rad:W	float32	73	0.000785	float	
direct_rad_1h:J	float32	73	0.000785	float	
effective_cloud_cover:p	float32	73	0.000785	float	
elevation:m	float32	73	0.000785	float	
estimated_diff_hours	float64	73	0.000785	float	
fresh_snow_12h:cm	float32	73	0.000785	float	
fresh_snow_1h:cm	float32	73	0.000785	float	
fresh_snow_24h:cm	float32	73	0.000785	float	
fresh_snow_3h:cm	float32	73	0.000785	float	
fresh_snow_6h:cm	float32	73	0.000785	float	
hour	int64			int	
is_day:idx	float32	73	0.000785	float	
is_in_shadow:idx	float32	73	0.000785	float	
location	object			object	
month	int64			int	
msl_pressure:hPa	float32	73	0.000785	float	
precip_5min:mm	float32	73	0.000785	float	

precip_type_5min:idx	float32	73	0.000785	float
pressure_100m:hPa	float32	73	0.000785	float
pressure_50m:hPa	float32	73	0.000785	float
prob_rime:p	float32	73	0.000785	float
rain_water:kgm2	float32	73	0.000785	float
relative_humidity_1000hPa:p	float32	73	0.000785	float
sfc_pressure:hPa	float32	73	0.000785	float
snow_depth:cm	float32	73	0.000785	float
snow_melt_10min:mm	float32	73	0.000785	float
snow_water:kgm2	float32	73	0.000785	float
sun_azimuth:d	float32	73	0.000785	float
sun_elevation:d	float32	73	0.000785	float
super_cooled_liquid_water:kgm2	float32	73	0.000785	float
t_1000hPa:K	float32	73	0.000785	float
total_cloud_cover:p	float32	73	0.000785	float
visibility:m	float32	73	0.000785	float
weekday	int64			int
wind_speed_10m:ms	float32	73	0.000785	float
wind_speed_u_10m:ms	float32	73	0.000785	float
wind_speed_v_10m:ms	float32	73	0.000785	float
wind_speed_w_1000hPa:ms	float32	73	0.000785	float
y	float64			float
year	int64			int

	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	
dew_or_rime:idx	category	
dew_point_2m:K	numeric	
diffuse_rad:W	numeric	
diffuse_rad_1h:J	numeric	
direct_rad:W	numeric	
direct_rad_1h:J	numeric	
effective_cloud_cover:p	numeric	
elevation:m	category	
estimated_diff_hours	numeric	
fresh_snow_12h:cm	numeric	
fresh_snow_1h:cm	numeric	
fresh_snow_24h:cm	numeric	
fresh_snow_3h:cm	numeric	
fresh_snow_6h:cm	numeric	
hour	numeric	
is_day:idx	category	
is_in_shadow:idx	category	

location	category
month	category
msl_pressure:hPa	numeric
precip_5min:mm	numeric
precip_type_5min:idx	category
pressure_100m:hPa	numeric
pressure_50m:hPa	numeric
prob_rime:p	numeric
rain_water:kgm2	category
relative_humidity_1000hPa:p	numeric
sfc_pressure:hPa	numeric
snow_depth:cm	numeric
snow_melt_10min:mm	category
snow_water:kgm2	numeric
sun_azimuth:d	numeric
sun_elevation:d	numeric
super_cooled_liquid_water:kgm2	category
t_1000hPa:K	numeric
total_cloud_cover:p	numeric
visibility:m	numeric
weekday	category
wind_speed_10m:ms	numeric
wind_speed_u_10m:ms	numeric
wind_speed_v_10m:ms	numeric
wind_speed_w_1000hPa:ms	category
y	numeric
year	category

test_data dataset summary

	count	unique	top	freq	mean	\
absolute_humidity_2m:gm3	2160	106			8.206482	
air_density_2m:kgm3	2160	153			1.232807	
ceiling_height_agl:m	1473	1391			2938.389648	
clear_sky_energy_1h:J	2160	1807			1227746.75	
clear_sky_rad:W	2160	1044			341.056641	
cloud_base_agl:m	1879	1771			1797.160156	
dew_or_rime:idx	2160	3			0.040741	
dew_point_2m:K	2160	202			280.783203	
diffuse_rad:W	2160	985			84.915688	
diffuse_rad_1h:J	2160	1806			305696.5	
direct_rad:W	2160	916			114.279816	
direct_rad_1h:J	2160	1634			411408.875	
effective_cloud_cover:p	2160	590			64.113792	
elevation:m	2160	3			12.333333	
estimated_diff_hours	2160	24			27.5	
fresh_snow_12h:cm	2160	2			0.000185	
fresh_snow_1h:cm	2160	2			0.000185	
fresh_snow_24h:cm	2160	2			0.000185	

fresh_snow_3h:cm	2160	2			0.000185
fresh_snow_6h:cm	2160	2			0.000185
hour	2160	24			11.5
is_day:idx	2160	2			0.795833
is_in_shadow:idx	2160	2			0.24537
location	2160	3	A	720	
month	2160	3			5.666667
msl_pressure:hPa	2160	321			1016.805786
precip_5min:mm	2160	27			0.00775
precip_type_5min:idx	2160	3			0.065741
pressure_100m:hPa	2160	359			1002.970825
pressure_50m:hPa	2160	356			1009.007202
prob_rime:p	2160	3			0.01588
rain_water:kgm2	2160	8			0.013056
relative_humidity_1000hPa:p	2160	538			70.920792
sfc_pressure:hPa	2160	363			1015.070374
snow_depth:cm	2160	1			0.0
snow_melt_10min:mm	2160	1			0.0
snow_water:kgm2	2160	16			0.060972
sun_azimuth:d	2160	1830			183.166199
sun_elevation:d	2160	1623			20.292332
super_cooled_liquid_water:kgm2	2160	7			0.065463
t_1000hPa:K	2160	254			284.737732
total_cloud_cover:p	2160	553			69.298981
visibility:m	2160	2155			33304.636719
weekday	2160	7			3.233333
wind_speed_10m:ms	2160	83			2.946759
wind_speed_u_10m:ms	2160	123			1.650694
wind_speed_v_10m:ms	2160	80			-0.187176
wind_speed_w_1000hPa:ms	2160	2			0.000324
year	2160	1			2023.0

	std	min	25% \
absolute_humidity_2m:gm3	2.201396	3.2	6.6
air_density_2m:kgm3	0.032116	1.142	1.209
ceiling_height_agl:m	2913.641113	30.6	891.799988
clear_sky_energy_1h:J	1104468.625	0.0	64338.124023
clear_sky_rad:W	307.729095	0.0	13.65
cloud_base_agl:m	2046.394409	29.799999	486.899994
dew_or_rime:idx	0.202365	-1.0	0.0
dew_point_2m:K	4.378817	268.0	277.899994
diffuse_rad:W	78.422508	0.0	6.925
diffuse_rad_1h:J	278146.25	0.0	36756.901367
direct_rad:W	171.838226	0.0	0.0
direct_rad_1h:J	611480.125	0.0	86.575001
effective_cloud_cover:p	37.947498	0.0	30.700001
elevation:m	8.261587	6.0	6.0
estimated_diff_hours	6.923789	16.0	21.75

fresh_snow_12h:cm	0.008607	0.0	0.0
fresh_snow_1h:cm	0.008607	0.0	0.0
fresh_snow_24h:cm	0.008607	0.0	0.0
fresh_snow_3h:cm	0.008607	0.0	0.0
fresh_snow_6h:cm	0.008607	0.0	0.0
hour	6.923789	0.0	5.75
is_day:idx	0.403185	0.0	1.0
is_in_shadow:idx	0.430406	0.0	0.0
location			
month	0.596423	5.0	5.0
msl_pressure:hPa	9.728754	986.099976	1011.5
precip_5min:mm	0.033776	0.0	0.0
precip_type_5min:idx	0.249747	0.0	0.0
pressure_100m:hPa	9.644145	971.799988	997.799988
pressure_50m:hPa	9.74076	977.700012	1003.799988
prob_rime:p	0.551282	0.0	0.0
rain_water:kgm2	0.055256	0.0	0.0
relative_humidity_1000hPa:p	15.725973	23.9	60.275
sfc_pressure:hPa	9.840412	983.5	1009.799988
snow_depth:cm	0.0	0.0	0.0
snow_melt_10min:mm	0.0	-0.0	-0.0
snow_water:kgm2	0.219562	0.0	0.0
sun_azimuth:d	109.193207	8.27	85.359253
sun_elevation:d	18.681047	-11.617	1.96475
super_cooled_liquid_water:kgm2	0.115824	0.0	0.0
t_1000hPa:K	5.839595	273.700012	279.799988
total_cloud_cover:p	38.41222	0.0	32.799999
visibility:m	15624.633789	874.400024	19635.100098
weekday	2.186573	0.0	1.0
wind_speed_10m:ms	1.733865	0.0	1.5
wind_speed_u_10m:ms	2.578466	-4.3	-0.2
wind_speed_v_10m:ms	1.50826	-4.4	-1.3
wind_speed_w_1000hPa:ms	0.005685	-0.0	0.0
year	0.0	2023.0	2023.0

	50%	75%	max \
absolute_humidity_2m:gm3	8.0	10.0	14.2
air_density_2m:kgm3	1.238	1.26	1.301
ceiling_height_agl:m	1553.900024	4021.300049	11468.0
clear_sky_energy_1h:J	1056303.125	2372037.5	3005707.0
clear_sky_rad:W	273.849991	646.874985	835.099976
cloud_base_agl:m	997.799988	2298.300049	11467.799805
dew_or_rime:idx	0.0	0.0	1.0
dew_point_2m:K	281.0	284.299988	290.200012
diffuse_rad:W	73.700001	135.600006	312.600006
diffuse_rad_1h:J	272526.046875	488256.03125	1086246.25
direct_rad:W	16.200001	180.399994	668.0
direct_rad_1h:J	60416.199219	686746.859375	2403444.25

```
effective_cloud_cover:p             77.75        100.0        100.0
elevation:m                           7.0         24.0         24.0
estimated_diff_hours                 27.5        33.25         39.0
fresh_snow_12h:cm                     0.0          0.0          0.4
fresh_snow_1h:cm                      0.0          0.0          0.4
fresh_snow_24h:cm                     0.0          0.0          0.4
fresh_snow_3h:cm                      0.0          0.0          0.4
fresh_snow_6h:cm                      0.0          0.0          0.4
hour                                 11.5        17.25         23.0
is_day:idx                            1.0          1.0          1.0
is_in_shadow:idx                      0.0          0.0          1.0
location
month                                 6.0          6.0          7.0
msl_pressure:hPa              1020.599976  1023.799988  1029.599976
precip_5min:mm                        0.0          0.0         0.34
precip_type_5min:idx                  0.0          0.0          2.0
pressure_100m:hPa                 1006.25  1010.099976  1016.400024
pressure_50m:hPa              1012.299988  1016.200012       1022.5
prob_rime:p                           0.0          0.0         23.0
rain_water:kgm2                       0.0          0.0          0.7
relative_humidity_1000hPa:p     73.900002    83.699997    98.900002
sfc_pressure:hPa              1018.299988  1022.299988  1028.699951
snow_depth:cm                         0.0          0.0          0.0
snow_melt_10min:mm                    0.0          0.0          0.0
snow_water:kgm2                       0.0          0.0          3.4
sun_azimuth:d                     184.236   279.576248   356.984009
sun_elevation:d                     18.54    38.102499       49.902
super_cooled_liquid_water:kgm2        0.0          0.1          0.6
t_1000hPa:K                    284.799988   288.299988   302.200012
total_cloud_cover:p             95.300003        100.0        100.0
visibility:m                 37623.050781 45378.099609 63863.800781
weekday                               3.0          5.0          6.0
wind_speed_10m:ms                     2.7          4.0          8.8
wind_speed_u_10m:ms                   1.6        3.525          8.8
wind_speed_v_10m:ms                  -0.3          0.8          4.0
wind_speed_w_1000hPa:ms               0.0          0.0          0.1
year                               2023.0       2023.0       2023.0

                                dtypes missing_count missing_ratio raw_type  \
absolute_humidity_2m:gm3       float32                                float
air_density_2m:kgm3            float32                                float
ceiling_height_agl:m           float32           687      0.318056    float
clear_sky_energy_1h:J          float32                                float
clear_sky_rad:W                float32                                float
cloud_base_agl:m               float32           281      0.130093    float
dew_or_rime:idx                float32                                float
dew_point_2m:K                 float32                                float
diffuse_rad:W                  float32                                float
```

diffuse_rad_1h:J	float32	float
direct_rad:W	float32	float
direct_rad_1h:J	float32	float
effective_cloud_cover:p	float32	float
elevation:m	float32	float
estimated_diff_hours	int64	int
fresh_snow_12h:cm	float32	float
fresh_snow_1h:cm	float32	float
fresh_snow_24h:cm	float32	float
fresh_snow_3h:cm	float32	float
fresh_snow_6h:cm	float32	float
hour	int64	int
is_day:idx	float32	float
is_in_shadow:idx	float32	float
location	object	object
month	int64	int
msl_pressure:hPa	float32	float
precip_5min:mm	float32	float
precip_type_5min:idx	float32	float
pressure_100m:hPa	float32	float
pressure_50m:hPa	float32	float
prob_rime:p	float32	float
rain_water:kgm2	float32	float
relative_humidity_1000hPa:p	float32	float
sfc_pressure:hPa	float32	float
snow_depth:cm	float32	float
snow_melt_10min:mm	float32	float
snow_water:kgm2	float32	float
sun_azimuth:d	float32	float
sun_elevation:d	float32	float
super_cooled_liquid_water:kgm2	float32	float
t_1000hPa:K	float32	float
total_cloud_cover:p	float32	float
visibility:m	float32	float
weekday	int64	int
wind_speed_10m:ms	float32	float
wind_speed_u_10m:ms	float32	float
wind_speed_v_10m:ms	float32	float
wind_speed_w_1000hPa:ms	float32	float
year	int64	int

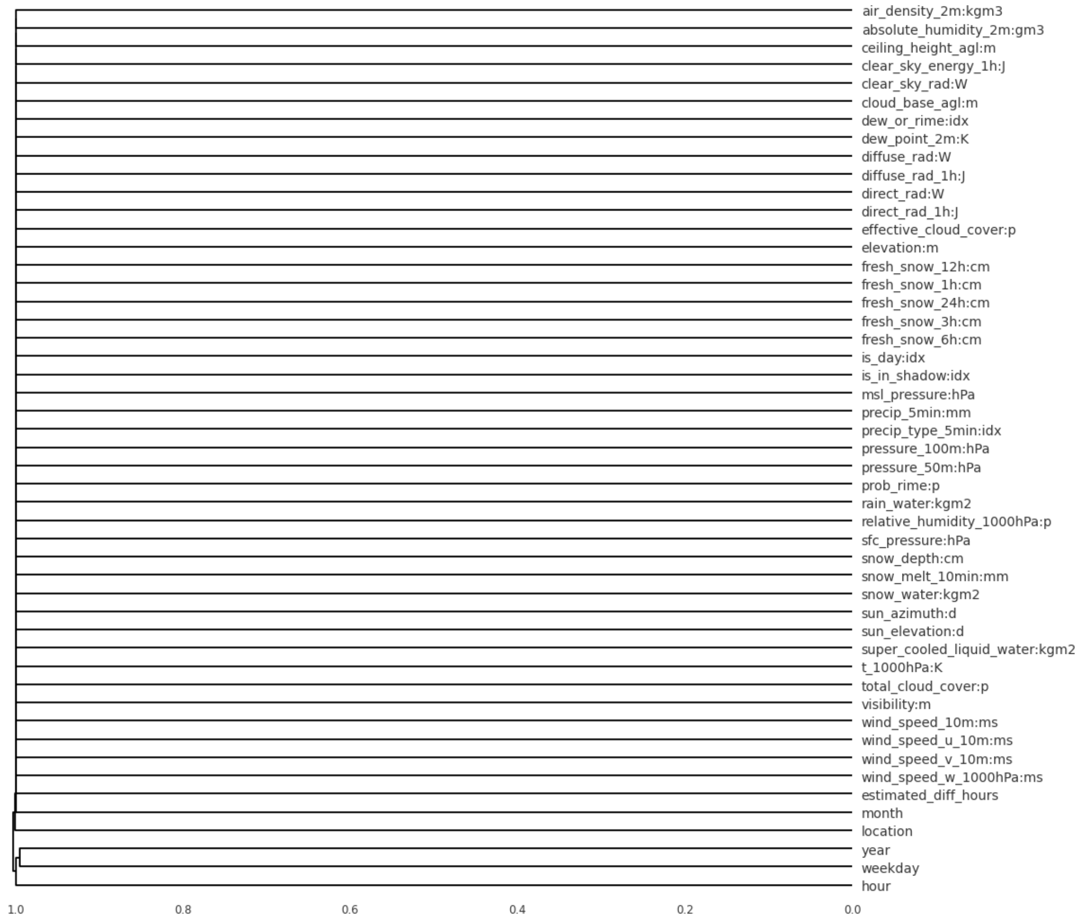
	variable_type	special_types
absolute_humidity_2m:gm3	numeric	
air_density_2m:kgm3	numeric	
ceiling_height_agl:m	numeric	
clear_sky_energy_1h:J	numeric	
clear_sky_rad:W	numeric	
cloud_base_agl:m	numeric	

```
dew_or_rime:idx                    category
dew_point_2m:K                      numeric
diffuse_rad:W                       numeric
diffuse_rad_1h:J                    numeric
direct_rad:W                        numeric
direct_rad_1h:J                     numeric
effective_cloud_cover:p             numeric
elevation:m                        category
estimated_diff_hours                numeric
fresh_snow_12h:cm                  category
fresh_snow_1h:cm                   category
fresh_snow_24h:cm                  category
fresh_snow_3h:cm                   category
fresh_snow_6h:cm                   category
hour                                numeric
is_day:idx                         category
is_in_shadow:idx                   category
location                           category
month                              category
msl_pressure:hPa                    numeric
precip_5min:mm                      numeric
precip_type_5min:idx               category
pressure_100m:hPa                   numeric
pressure_50m:hPa                    numeric
prob_rime:p                        category
rain_water:kgm2                    category
relative_humidity_1000hPa:p         numeric
sfc_pressure:hPa                    numeric
snow_depth:cm                      category
snow_melt_10min:mm                 category
snow_water:kgm2                    category
sun_azimuth:d                       numeric
sun_elevation:d                     numeric
super_cooled_liquid_water:kgm2     category
t_1000hPa:K                         numeric
total_cloud_cover:p                 numeric
visibility:m                        numeric
weekday                            category
wind_speed_10m:ms                   numeric
wind_speed_u_10m:ms                 numeric
wind_speed_v_10m:ms                 numeric
wind_speed_w_1000hPa:ms            category
year                               category
```

Types warnings summary

```
                     train_data test_data warnings
estimated_diff_hours      float       int  warning
y                         float        --  warning
```

1.0.1 Feature Distance



2 Starting

[129]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
```

```
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 79
Now creating submission number: 80
New filename: submission_80_jorge
```

[130]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60
presets = 'best_quality'
```

```
Loaded data from: X_train_raw.csv | Columns = 51 / 51 | Rows = 93024 -> 93024
```

[131]:
```
predictors = [None, None, None]
```

[132]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
  ↪path=f"AutogluonModels/{new_filename}_{loc}").
  ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
  ↪presets=presets)
predictors[0] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_80_jorge_A/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   32.39 GB / 494.38 GB (6.6%)
Train Data Rows:    34085
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
```

```
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4955.58 MB
        Train Data (Original)  Memory Usage: 15.07 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.85 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
```

```
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.9s of the
59.87s of remaining time.

Training model for location A…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 134.02s compared to 51.85s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.89s of the
57.86s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 115.1s compared to 49.23s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.16s of the
56.12s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -161.5323        = Validation score   (-mean_absolute_error)
        29.71s   = Training   runtime
        66.55s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.87s of the
14.85s of remaining time.
        -161.5323        = Validation score   (-mean_absolute_error)
        0.01s    = Training   runtime
        0.0s     = Validation runtime
```

```
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 14.82s of the
14.79s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -163.1923        = Validation score   (-mean_absolute_error)
        3.01s    = Training   runtime
        0.58s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 9.38s of the 9.36s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -161.4697        = Validation score   (-mean_absolute_error)
        1.57s    = Training   runtime
        0.18s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 6.0s of the
5.97s of remaining time.
        -161.1148        = Validation score   (-mean_absolute_error)
        24.64s   = Training   runtime
        0.87s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.87s of the
-19.78s of remaining time.
        -159.5898        = Validation score   (-mean_absolute_error)
        0.13s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 79.93s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_80_jorge_A/")
```

[133]:
```python
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[1] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_80_jorge_B/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
```

```
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   31.67 GB / 494.38 GB (6.4%)
Train Data Rows:    32844
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.82478, 193.94649)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4422.96 MB
        Train Data (Original)  Memory Usage: 14.52 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
```

```
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 12.38 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.1s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.92s of the
59.89s of remaining time.

Training model for location B…

        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 134.58s compared to 51.87s of available time.
        Time limit exceeded… Skipping KNeighborsUnif_BAG_L1.
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.81s of the
57.78s of remaining time.
        Not enough time to generate out-of-fold predictions for model. Estimated
time required was 181.34s compared to 49.13s of available time.
        Time limit exceeded… Skipping KNeighborsDist_BAG_L1.
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 35.01s of the
54.98s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
```

```
ParallelLocalFoldFittingStrategy
        -25.7449         = Validation score   (-mean_absolute_error)
        28.13s   = Training   runtime
        61.8s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.9s of the
16.53s of remaining time.
        -25.7449         = Validation score   (-mean_absolute_error)
        0.0s     = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 16.52s of the
16.51s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -24.2516         = Validation score   (-mean_absolute_error)
        5.37s    = Training   runtime
        1.17s    = Validation runtime
Fitting model: LightGBM_BAG_L2 … Training model for up to 8.31s of the 8.31s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -23.6458         = Validation score   (-mean_absolute_error)
        1.99s    = Training   runtime
        0.18s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L2 … Training model for up to 3.95s of the
3.94s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        24.97s   = Training   runtime
        0.85s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.9s of the
-22.07s of remaining time.
        -22.1865         = Validation score   (-mean_absolute_error)
        0.12s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 82.21s … Best model:
"WeightedEnsemble_L3"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_80_jorge_B/")
```

[134]:
```
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
↪path=f"AutogluonModels/{new_filename}_{loc}").
↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
↪presets=presets)
```

```python
predictors[2] = predictor
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_80_jorge_C/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   31.05 GB / 494.38 GB (6.3%)
Train Data Rows:    26095
Train Data Columns: 49
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 77.63106, 165.81688)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    4564.21 MB
        Train Data (Original)  Memory Usage: 11.53 MB (0.3% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
```

```
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  4 | ['hour', 'weekday', 'month', 'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  1 | ['elevation:m']
        0.1s = Fit runtime
        48 features in original data used to generate 48 features in processed
data.
        Train Data (Processed) Memory Usage: 9.84 MB (0.2% of available memory)
Data preprocessing and feature engineering runtime = 0.12s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.91s of the
59.88s of remaining time.
```

```
Training model for location C…
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

```
Loaded data from: X_train_raw.csv | Columns = 51 / 51 | Rows = 93024 -> 93024
Loaded data from: X_test_raw.csv | Columns = 50 / 50 | Rows = 2160 -> 2160
```

[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
↪"location"], left_on=["ds", "location"])

#test_data_merged
```

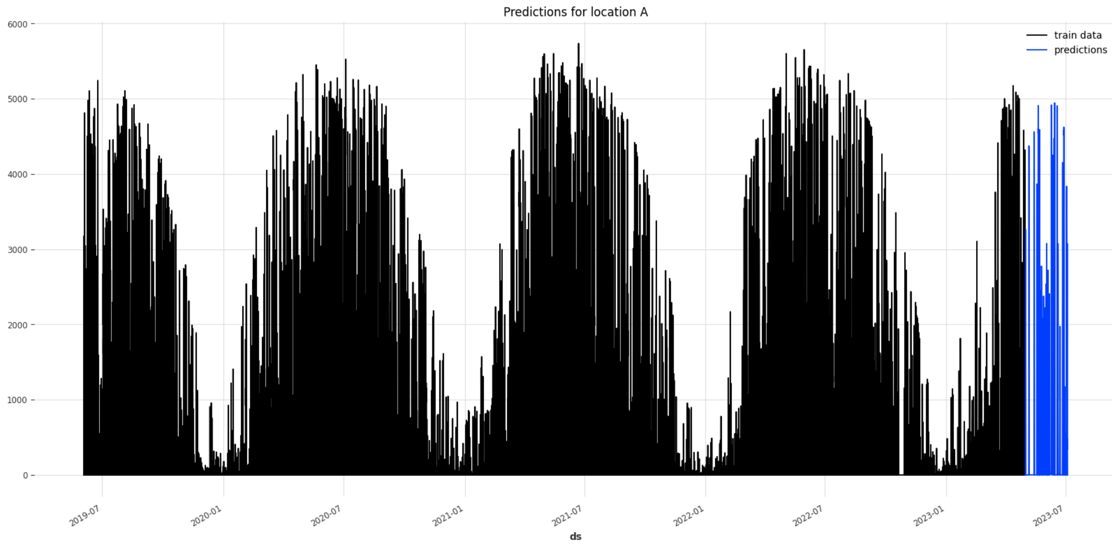
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

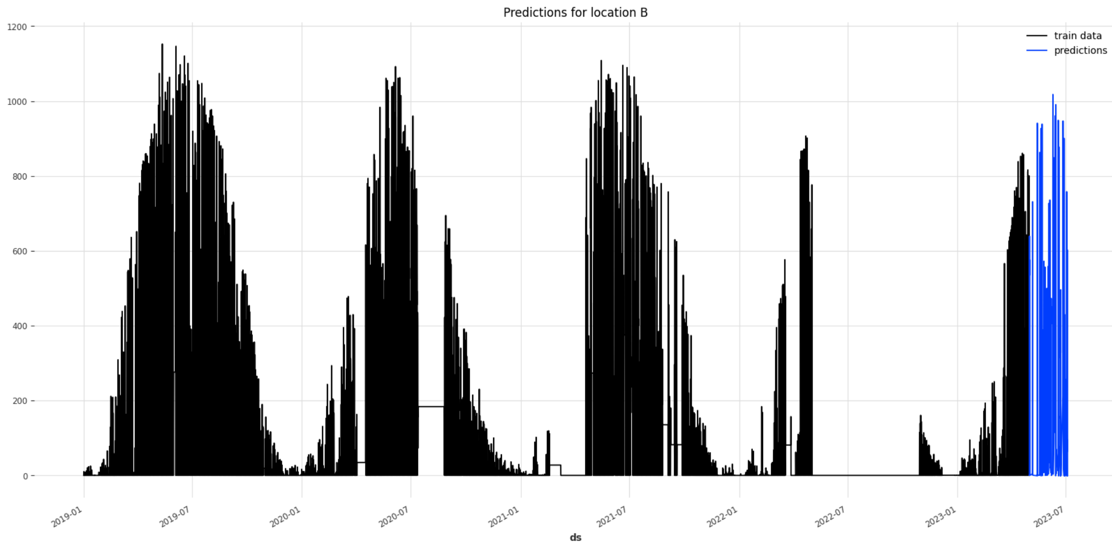
[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)
```

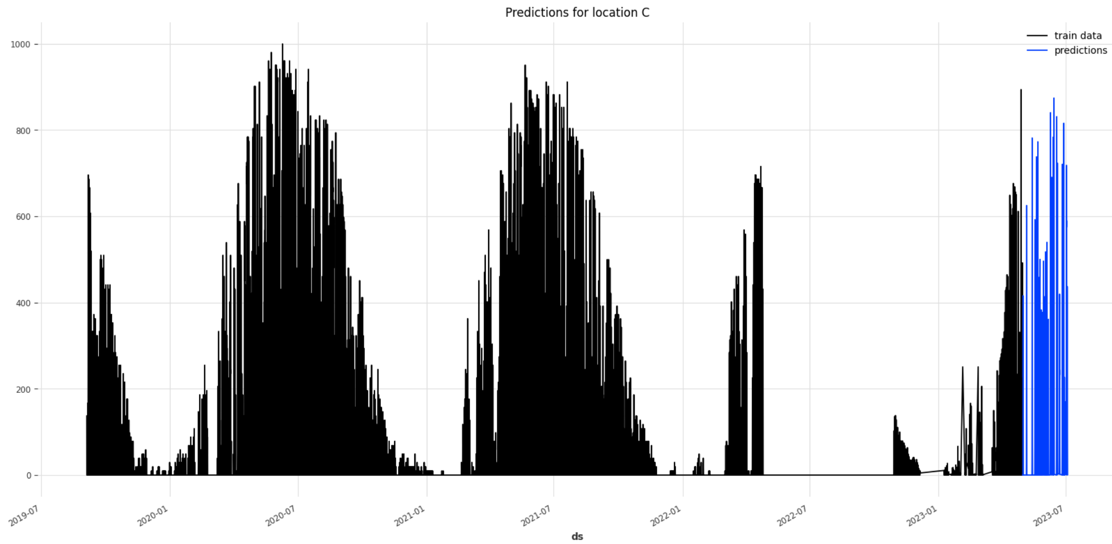
[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='y', ax=ax, label="train data")
```

```python
# plot predictions
predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

# title
ax.set_title(f"Predictions for location {loc}")
```







[ ]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
       id  prediction
0       0    1.566077
1       1    1.583403
2       2    1.765823
3       3   46.396004
4       4  295.959717
..    ...         ...
715  2155   90.709702
716  2156   57.039017
717  2157   21.729446
718  2158    2.949956
719  2159    1.334793

[2160 rows x 2 columns]
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),
↪index=False)
```

```
Saving submission to submissions/submission_79_jorge.csv
```

[ ]:
```python
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_79_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_79_jorge_files/notebook_pdfs
[NbConvertApp] Writing 163602 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/data/autogluon_each_location.ipynb Cell 1␣
↪line 4
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#X41sZmlsZQ%3D%3D?line=1'>2</a> import subprocess
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#X41sZmlsZQ%3D%3D?line=2'>3</a> import os
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#X41sZmlsZQ%3D%3D?line=3'>4</a> subprocess.
↪run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.ipynb"])

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/subprocess.py:505, in␣
↪run(input, capture_output, timeout, check, *popenargs, **kwargs)
    503 with Popen(*popenargs, **kwargs) as process:
    504     try:
--> 505         stdout, stderr = process.communicate(input, timeout=timeout)
    506     except TimeoutExpired as exc:
    507         process.kill()

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/subprocess.py:1146, in Popen.
↪communicate(self, input, timeout)
   1144         stderr = self.stderr.read()
   1145         self.stderr.close()
-> 1146     self.wait()
   1147 else:
   1148     if timeout is not None:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/subprocess.py:1209, in Popen.
↪wait(self, timeout)
   1207     endtime = _time() + timeout
   1208 try:
```

```
-> 1209     return self._wait(timeout=timeout)
   1210 except KeyboardInterrupt:
   1211     # https://bugs.python.org/issue25942
   1212     # The first keyboard interrupt waits briefly for the child to
   1213     # exit under the common assumption that it also received the ^C
   1214     # generated SIGINT and will exit rapidly.
   1215     if timeout is not None:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/subprocess.py:1959, in Pope .
↪_wait(self, timeout)
   1957 if self.returncode is not None:
   1958     break  # Another thread waited.
-> 1959 (pid, sts) = self._try_wait(0)
   1960 # Check the pid and loop as waitpid has been known to
   1961 # return 0 even without WNOHANG in odd situations.
   1962 # http://bugs.python.org/issue14396.
   1963 if pid == self.pid:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/subprocess.py:1917, in Pope .
↪_try_wait(self, wait_flags)
   1915 """All callers to this function MUST hold self._waitpid_lock."""
   1916 try:
-> 1917     (pid, sts) = os.waitpid(self.pid, wait_flags)
   1918 except ChildProcessError:
   1919     # This happens if SIGCLD is set to be ignored or waiting
   1920     # for child processes has otherwise been disabled for our
   1921     # process.  This child is dead, we can't get the status.
   1922     pid = self.pid

KeyboardInterrupt:
```

[ ]:
```
# feature importance
predictors[0].feature_importance(feature_stage="original",␣
↪data=train_data[train_data["location"] == "A"])
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['snow_drift:idx', 'location']
Computing feature importance via permutation shuffling for 45 features using
5000 rows with 5 shuffle sets…
        1015.74s        = Expected runtime (203.15s per shuffle set)
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/data/autogluon_each_location.ipynb Cell 2 ␣
↪line 2
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#X36sZmlsZQ%3D%3D?line=0'>1</a> # feature␣
↪importance
```

```
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/data/
↪autogluon_each_location.ipynb#X36sZmlsZQ%3D%3D?line=1'>2</a> predictors[0].
↪feature_importance(feature_stage="original",␣
↪data=train_data[train_data["location"] == "A"])

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/predictor/predictor.py:2425, in TabularPredictor.
↪feature_importance(self, data, model, features, feature_stage, subsample_size␣
↪time_limit, num_shuffle_sets, include_confidence_band, confidence_level,␣
↪silent)
   2422 if num_shuffle_sets is None:
   2423     num_shuffle_sets = 10 if time_limit else 5
-> 2425 fi_df = self._learner.get_feature_importance(
   2426     model=model,
   2427     X=data,
   2428     features=features,
   2429     feature_stage=feature_stage,
   2430     subsample_size=subsample_size,
   2431     time_limit=time_limit,
   2432     num_shuffle_sets=num_shuffle_sets,
   2433     silent=silent,
   2434 )
   2436 if include_confidence_band:
   2437     if confidence_level <= 0.5 or confidence_level >= 1.0:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/learner/abstract_learner.py:870, in AbstractTabularLearner.
↪get_feature_importance(self, model, X, y, features, feature_stage,␣
↪subsample_size, silent, **kwargs)
    867         X = X.drop(columns=unused_features)
    869     if feature_stage == "original":
--> 870         return trainer._get_feature_importance_raw(
    871             model=model, X=X, y=y, features=features,␣
↪subsample_size=subsample_size, transform_func=self.transform_features,␣
↪silent=silent, **kwargs
    872         )
    873     X = self.transform_features(X)
    874 else:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪trainer/abstract_trainer.py:2574, in AbstractTrainer.
↪_get_feature_importance_raw(self, X, y, model, eval_metric, **kwargs)
   2572 model: AbstractModel = self.load_model(model)
   2573 predict_func_kwargs = dict(model=model)
-> 2574 return compute_permutation_feature_importance(
   2575     X=X,
   2576     y=y,
   2577     predict_func=predict_func,
   2578     predict_func_kwargs=predict_func_kwargs,
   2579     eval_metric=eval_metric,
```

```
   2580     quantile_levels=self.quantile_levels,
   2581     **kwargs,
   2582 )

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪utils/utils.py:867, in compute_permutation_feature_importance(X, y,␣
 ↪predict_func, eval_metric, features, subsample_size, num_shuffle_sets,␣
 ↪predict_func_kwargs, transform_func, transform_func_kwargs, time_limit,␣
 ↪silent, log_prefix, importance_as_list, random_state, **kwargs)
    865 else:
    866     X_raw_transformed = X_raw if transform_func is None else␣
 ↪transform_func(X_raw, **transform_func_kwargs)
--> 867 y_pred = predict_func(X_raw_transformed, **predict_func_kwargs)
    869 row_index = 0
    870 for feature in parallel_computed_features:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:749, in AbstractTrainer.predict(self, X, model)
    747     model = self._get_best()
    748 cascade = isinstance(model, list)
--> 749 return self._predict_model(X, model, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2388, in AbstractTrainer._predict_model(self, X,␣
 ↪model, model_pred_proba_dict, cascade)
   2387 def _predict_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2388     y_pred_proba = self._predict_proba_model(X=X, model=model,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
   2389     return get_pred_from_proba(y_pred_proba=y_pred_proba,␣
 ↪problem_type=self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2392, in AbstractTrainer.
 ↪_predict_proba_model(self, X, model, model_pred_proba_dict, cascade)
   2391 def _predict_proba_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2392     return self.get_pred_proba_from_model(model=model, X=X,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:769, in AbstractTrainer.
 ↪get_pred_proba_from_model(self, model, X, model_pred_proba_dict, cascade)
    767 else:
    768     models = [model]
--> 769 model_pred_proba_dict = self.get_model_pred_proba_dict(X=X,␣
 ↪models=models, model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
    770 if not isinstance(model, str):
    771     model = model.name
```

```
File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪trainer/abstract_trainer.py:1018, in AbstractTrainer.
↪get_model_pred_proba_dict(self, X, models, model_pred_proba_dict,␣
↪model_pred_time_dict, record_pred_time, use_val_cache, cascade,␣
↪cascade_threshold)
   1016     else:
   1017         preprocess_kwargs = dict(infer=False,␣
↪model_pred_proba_dict=model_pred_proba_dict)
-> 1018     model_pred_proba_dict[model_name] = model.predict_proba(X,␣
↪**preprocess_kwargs)
   1019 else:
   1020     model_pred_proba_dict[model_name] = model.predict_proba(X)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/ensemble/bagged_ensemble_model.py:349, in BaggedEnsembleModel.
↪predict_proba(self, X, normalize, **kwargs)
    347 for model in self.models[1:]:
    348     model = self.load_child(model)
--> 349     pred_proba += model.predict_proba(X=X, preprocess_nonadaptive=False,␣
↪normalize=normalize)
    350 pred_proba = pred_proba / len(self.models)
    352 if self.params_aux.get("temperature_scalar", None) is not None:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/abstract/abstract_model.py:931, in AbstractModel.predict_proba(self, X,␣
↪normalize, **kwargs)
    929 if normalize is None:
    930     normalize = self.normalize_pred_probas
--> 931 y_pred_proba = self._predict_proba(X=X, **kwargs)
    932 if normalize:
    933     y_pred_proba = normalize_pred_probas(y_pred_proba, self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/models/lgb/lgb_model.py:234, in LGBModel._predict_proba(self, X,␣
↪num_cpus, **kwargs)
    231 def _predict_proba(self, X, num_cpus=0, **kwargs):
    232     X = self.preprocess(X, **kwargs)
--> 234     y_pred_proba = self.model.predict(X, num_threads=num_cpus)
    235     if self.problem_type == REGRESSION:
    236         return y_pred_proba

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:3538, in Booster.predict(self, data, start_iteration, num_iteration,␣
↪raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape, **kwargs)
   3536     else:
   3537         num_iteration = -1
-> 3538 return predictor.predict(data, start_iteration, num_iteration,
   3539                          raw_score, pred_leaf, pred_contrib,
```

```
   3540                             data_has_header, is_reshape)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
 ↪py:848, in _InnerPredictor.predict(self, data, start_iteration, num_iteration,␣
 ↪raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape)
    846     preds, nrow = self.__pred_for_csc(data, start_iteration,␣
 ↪num_iteration, predict_type)
    847 elif isinstance(data, np.ndarray):
--> 848     preds, nrow = self.__pred_for_np2d(data, start_iteration,␣
 ↪num_iteration, predict_type)
    849 elif isinstance(data, list):
    850     try:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
 ↪py:938, in _InnerPredictor.__pred_for_np2d(self, mat, start_iteration,␣
 ↪num_iteration, predict_type)
    936     return preds, nrow
    937 else:
--> 938     return inner_predict(mat, start_iteration, num_iteration,␣
 ↪predict_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
 ↪py:908, in _InnerPredictor.__pred_for_np2d.<locals>.inner_predict(mat,␣
 ↪start_iteration, num_iteration, predict_type, preds)
    906     raise ValueError("Wrong length of pre-allocated predict array")
    907 out_num_preds = ctypes.c_int64(0)
--> 908 _safe_call(_LIB.LGBM_BoosterPredictForMat(
    909     self.handle,
    910     ptr_data,
    911     ctypes.c_int(type_ptr_data),
    912     ctypes.c_int32(mat.shape[0]),
    913     ctypes.c_int32(mat.shape[1]),
    914     ctypes.c_int(C_API_IS_ROW_MAJOR),
    915     ctypes.c_int(predict_type),
    916     ctypes.c_int(start_iteration),
    917     ctypes.c_int(num_iteration),
    918     c_str(self.pred_parameter),
    919     ctypes.byref(out_num_preds),
    920     preds.ctypes.data_as(ctypes.POINTER(ctypes.c_double))))
    921 if n_preds != out_num_preds.value:
    922     raise ValueError("Wrong length for predict results")

KeyboardInterrupt:
```

[ ]:
```
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
 ↪"autogluon_each_location.ipynb"])
```

```
[NbConvertApp] Converting notebook autogluon_each_location.ipynb to pdf
[NbConvertApp] Support files will be in notebook_pdfs/submission_78_jorge_files/
[NbConvertApp] Making directory
./notebook_pdfs/submission_78_jorge_files/notebook_pdfs
[NbConvertApp] Writing 76131 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 251165 bytes to notebook_pdfs/submission_78_jorge.pdf
```

[ ]:
```
CompletedProcess(args=['jupyter', 'nbconvert', '--to', 'pdf', '--output',
'notebook_pdfs/submission_78_jorge.pdf', 'autogluon_each_location.ipynb'],
returncode=0)
```